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Forecasting the Cost of Electricity Generated by Offshore Wind Turbines

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Forecasting the Cost of Electricity Generated by Offshore Wind Turbines

A Thesis Presented by

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ABSTRACT

FORECASTING THE COST OF ELECTRICITY GENERATED BY OFFSHORE WIND TURBINES

MAY 2019

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To impede the progress of climate change, many policy makers are considering avenues to decarbonize electricity production. In addition to decarbonization, policy makers must consider how the cost of electricity will impact various stakeholders, balancing cost and social benefits. Offshore wind farms have the potential to produce affordable, carbon-free electricity, but they are a relatively new technology. The relative juvenescence of offshore wind lends itself to an uncertain future, regarding production costs. In this thesis, we seek to understand cost drivers behind offshore wind electricity by analyzing historic trends in offshore wind levelized cost of electricity (LCOE) through learning curves, characterizing how learning from producing a technology can lead to decreases in production costs. Additionally, we explore how the maturity of component technologies can affect the learning rate, and consequently the benefits of learning, of offshore wind. Finally, we create a robust data set to inform decision makers and researchers by marrying historic data to forward-looking expert elicitations.

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CHAPTER 1

INTRODUCTION

As human kind continues to grow and prosper, so does our reliance on electricity. Traditional sources of electricity, such as coal, oil, and natural gas, produce carbon dioxide that pollutes the atmosphere. Since 1950, carbon dioxide levels have increased by more than 30% [1,2]. To combat this pollution, policy makers around the world are taking steps to promote low-carbon, green technologies [3].

Among these green technologies, offshore wind turbines have considerable potential to produce affordable and efficient electricity. Compared to onshore wind, offshore wind resources tend to be stronger, have fewer geographical issues preventing turbine construction, and as populations along the shore grow, so does the coastal electricity demand [4].

The objective of this thesis is to analyze trends in the cost of electricity produced by offshore wind turbines, to better understand the drivers of technological change, and to support policy decisions. We begin by building a global experience curve for offshore wind. This experience curve illustrates how the maturation of the technology affects its price by comparing the cumulative installed capacity of offshore wind on a global scale with the levelized cost of electricity (LCOE).

We then perform an analysis of offshore wind energy's sensitivity to the maturity of its component technologies. In many regards, offshore wind energy is like onshore wind energy [5,6]. As such, some aspects of offshore wind energy may already be mature, and the learning for these technologies may be different than newer technologies designed specifically for offshore wind. Understanding how the different maturities of the technologies affect the cost of wind energy is of vital importance, especially regarding research and development investments.

Finally, we compare the experience curves, which are representations of historical data, with expert elicitations, a research method that looks forward in time. Expert elicitations characterize uncertainty better than data sets that describe the past [7]. By combining these two methods, we create a more robust knowledge base that incorporates both historical data as well as forward looking studies.

The rest of the thesis follows as such. We describe our methodology in Chapter 2. In Chapter 3, we discuss our data. In Chapter 4, we present our findings. Finally, in Chapter 5, we discuss our conclusions and suggest potential future efforts.

CHAPTER 2
METHODOLOGY

In this chapter we present and compare two models for offshore wind cost trends. There is uncertainty about how we should model offshore wind's technological maturity. Thus, we create and test two models to see if either one better explains trends in offshore wind costs. First, in Chapter 2.1, we discuss the emerging technology model, where we treat offshore wind power as a new technology in terms of learning. We begin with a discussion of experience curves, then we describe the methods we use to calculate the levelized cost of electricity and the cumulative global installed capacity. Next, in Chapter 2.2, we discuss the hybrid technology model, and how we analyze the maturity of offshore wind through component technologies of varying maturity. Finally, we detail how we integrate expert elicitations with the learning curve models we create in Chapter 2.3.

2.1 Offshore Wind Energy Experience Curves

Experience curves are tools that help researchers, developers, and investors understand how learning from the production of a product can lower that product's cost. According to Ibenholt, "Such a curve shows the decline in costs of production as experience, and thereby learning, is gained" [8]. The curves show trends in cost as they relate to how much production has taken place.

Experience curves take the form of Equation 1, where N_t is the cumulative number of units produced at time, t, C_t is the average cost to produce the N_t^{th} unit, and b is the index of learning. This method uses Wright's Model (Equation 1) and studies the effects of cumulative production on costs. Experience curves are often plotted on log-log plots, as the production growth rate is expected to be exponential. As such, the curve plotted on a log-log plot would be a straight line with its slope equal to *-b*. The index of learning is estimated by fitting a least-squares polynomial to the logs of the capacity and LCOE data. The progress ratio, 2^{-b}, can be used to calculate the learning rate (LR), Equation 2 [9,10]. The LR is the relative cost reduction, $(C_{2N}-C_N)/C_N$, associated with a doubling of the cumulative production of a technology. Figure 1 shows an example of a general experience curve [9].

$$C_t = C_0 * \left(\frac{N_t}{N_0}\right)^{-b} \qquad \textbf{1}$$

$$LR = \frac{C_{2N}-C_N}{C_N} = 1 - 2^{-b} \qquad \textbf{2}$$

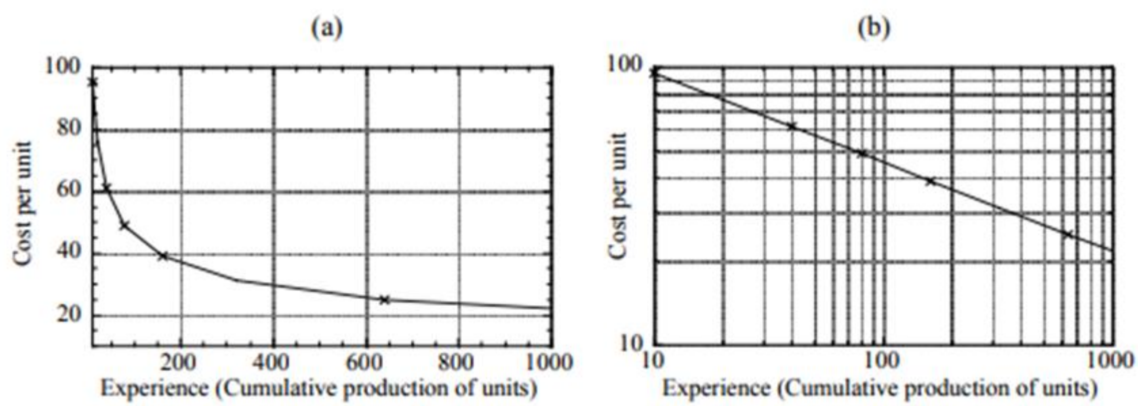

Figure 1: Example Learning Curves.. Two versions of the same experience curve showing how the cost per unit declines as more units are produced. (a) is plotted on a linear scale, while (b) is plotted on a log-log scale. The slope of the line in (b) is the learning rate, -b, in Equation 1 [9].

We use Wright's model to create an emerging technology model for offshore wind costs. In this model, we fit the historic data to find the learning rate. Our experience curves consider the levelized cost of electricity generated by offshore wind turbines as a function of the cumulative installed capacity. We discuss how we calculate the levelized cost of electricity and cumulative installed capacity in chapters 2.1.1 and 2.1.2

2.1.1 Levelized Cost of Electricity

Manwell et al. [11] suggest that three common models used to study the economics of offshore wind power are: simplified models, life cycle cost models, and electric utility economic models, each with its own strengths and weaknesses. We study the levelized cost of electricity (LCOE) of offshore wind, which falls under the category of life cycle cost models. LCOE represents the cost of electricity necessary to recover the expenses of building and installing an offshore wind project. As such, research and development efforts have been focused on minimizing LCOE [12]. We define LCOE mathematically in Equation 3, where T is the lifetime of the project, t is the year, I_t is the investment (i.e. capital cost) at time t, O_t is the operations cost, M_t is the maintenance cost, F_t is the interest expenditure, r is the discount rate, and E_t is the energy produced in year t [13]. For t greater than 0, we assume I_t is equal to zero.

$$LCOE = \frac{\sum_{t=0}^{T} \left(\frac{I_t + O_t + M_t + F_t}{(1+r)^t} \right)}{\sum_{t=0}^{T} \left(\frac{E_t}{(1+r)^t} \right)} \qquad 3$$

It is rare to find data on the LCOE for individual offshore wind projects in the literature. Most data reported in the literature take the forms of various components of the LCOE equation, most common of which are the capital expenditure, the capacity, and the capacity factor. For projects where LCOE was not reported directly, we use a simplified version of Equation 3, focusing on the capital cost as the basis for our LCOE calculations, and ignoring the operations and maintenance (O&M) cost, which is not always available. Capital expenditures, including the cost of the turbine, support structure, electrical infrastructure, and installations, account for about 80% of a project's total cost [14]. Our calculations take the form of Equation 4, where *C* is the capital expenditure in dollars per kilowatt, *CF* is the capacity factor of the project, and *(A/P, r, T)* is the capital recovery factor, given discount rate *r* and lifetime *T*, converting the quantity to an annual value. The factor of 1.2 accounts for the fact that the capital expenditures used in our calculations do not represent the entire cost of a project.

$$LCOE = 1.2 * \frac{C}{8760 * CF} * (\frac{A}{P}, r, T) \qquad \textbf{4}$$

The capital recovery factor, *(A/P, r, T)* is calculated using Equation 5 [15]. Here, *A* represents the annual value, *P* represents the present value, *r* represents the discount rate, and *T* represents the number of compounding periods. We use the weighted average cost of capital (WACC) as the discount rate [16]. WACC is the minimal representation of a firm's minimum acceptable rate of return (MARR) in after-tax economic studies [17]. We use the WACC value reported in Arwas et al. (2012) of 10% and an estimate of 20 years as the lifetime of an offshore wind turbine for the number of compounding periods [18,19].

$$(\frac{A}{P}, r, T) = \frac{r * (1+r)^T}{(1+r)^T - 1} \qquad \textbf{5}$$

The LCOE represents a standardized price with which to compare the historical prices. It is one half of the data necessary to construct an experience curve. We describe the other half, cumulative installed capacity, in Chapter 2.1.2.

2.1.2 Global Cumulative Installed Capacity

As discussed in Chapter 2.1, experience curves compare two key pieces of data: price and cumulative production. The production data informs how many units have been produced at a given time. It represents the learning that comes with producing more of a product. This learning, in most cases, directly affects the price of the product, usually decreasing it. For electricity, there are two possible kinds of production to consider, capacity and energy. In our LCOE calculations in Chapter 2.1.1, we consider only the capital costs, excluding the O&M costs. As such, cumulative capacity is the logical choice to represent the experience gained from production, as both cumulative capacity and capital expenditures represent singular actions.

We calculate the cumulative installed capacity by summing the capacity data of individual projects on both regional and global scales. Our capacity data come from the literature and are discussed in more detail in Chapter 3.

To calculate the cumulative installed capacity, that is the installed capacity as a function of time, we define an order to the projects in the capacity summation. We use project dates to order the individual projects. Most of the data regarding dates, however, includes only the year the project was completed. To order the data on a temporal scale finer than a year, we order the individual projects in a given year from smallest to largest. While this method is not perfect, it provides a consistent method for ordering the projects, assuming the projects become more ambitious as time goes on.

2.2 Effects of Maturity on Learning

Offshore wind is a relatively new technology. It appears to have some aspects in common, however, with other energy production technologies, such as onshore wind. As such, offshore wind may not be a purely emerging technology and may be a hybrid technology with strong foundations in more mature technologies. This may imply that there is less room for learning in offshore wind than in other emerging technologies; and that the learning is concentrated in certain components [20].

Successful technologies tend to follow similar trends in their developments, the technology life cycle (TLC). In the TLC, a technology starts as an emerging technology, grows into maturity, and eventually saturation [21,22]. This is illustrated in Figure 2, below [21]. As a technology emerges and grows, it experiences a period of exponential growth in its implementation. After a certain point, however, it reaches maturity. In this period, the growth in implementation of the technology slows, eventually stagnating as implementation of the technology becomes saturated.

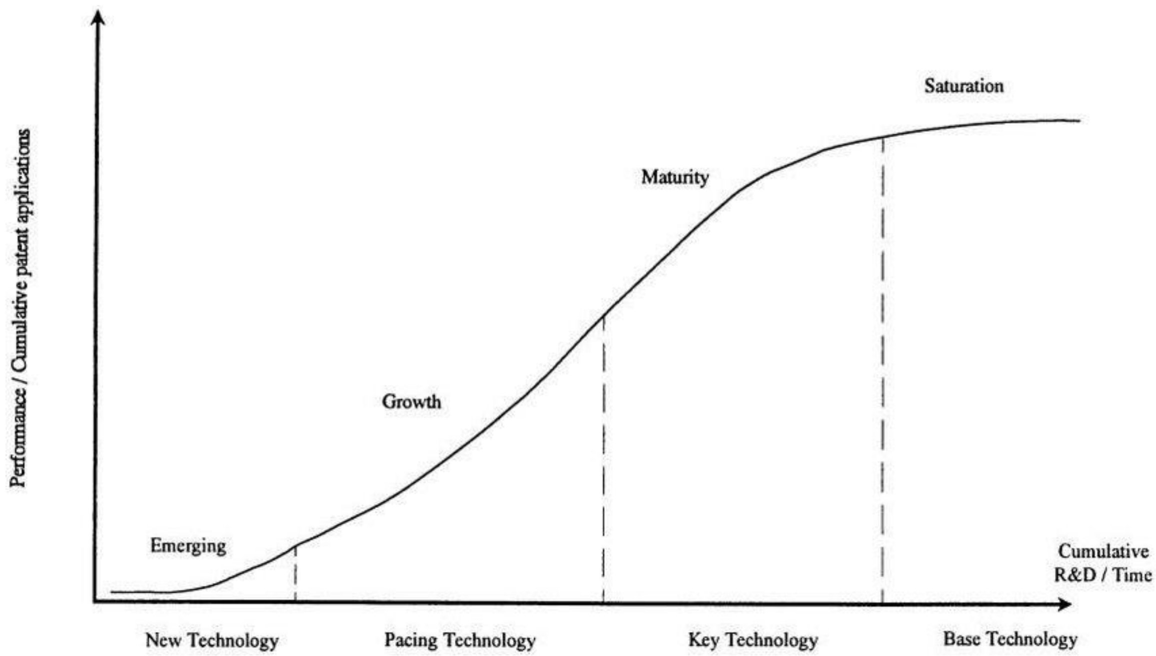

Figure 2: Technology Life Cycle S Curve. This plot shows how the adoption of a general technology is related to its development and how it can move from a new, emerging technology, to a more mature technology, eventually saturating its development. It's likely that onshore wind and offshore wind exist in areas of the curve before maturity, with onshore wind further along [21].

We assume that both onshore and offshore wind exist on TLC curves. In Figure 3, below, we show that both technologies are in periods of exponential growth in their implementations. As such, neither technology has reached a point of maturity. Assuming the shape of the TLC curves are the same, however, onshore wind is much further along than offshore wind. Based on the shape of onshore wind's curve in Figure 3, it is likely in the growing phase of its life cycle, potentially even approaching the maturity phase. Offshore wind, on the other hand, is likely still in the emerging phase and may be approaching the growth phase. It appears to be about where onshore wind was in the year 2000. As such, onshore wind is more mature than offshore wind.

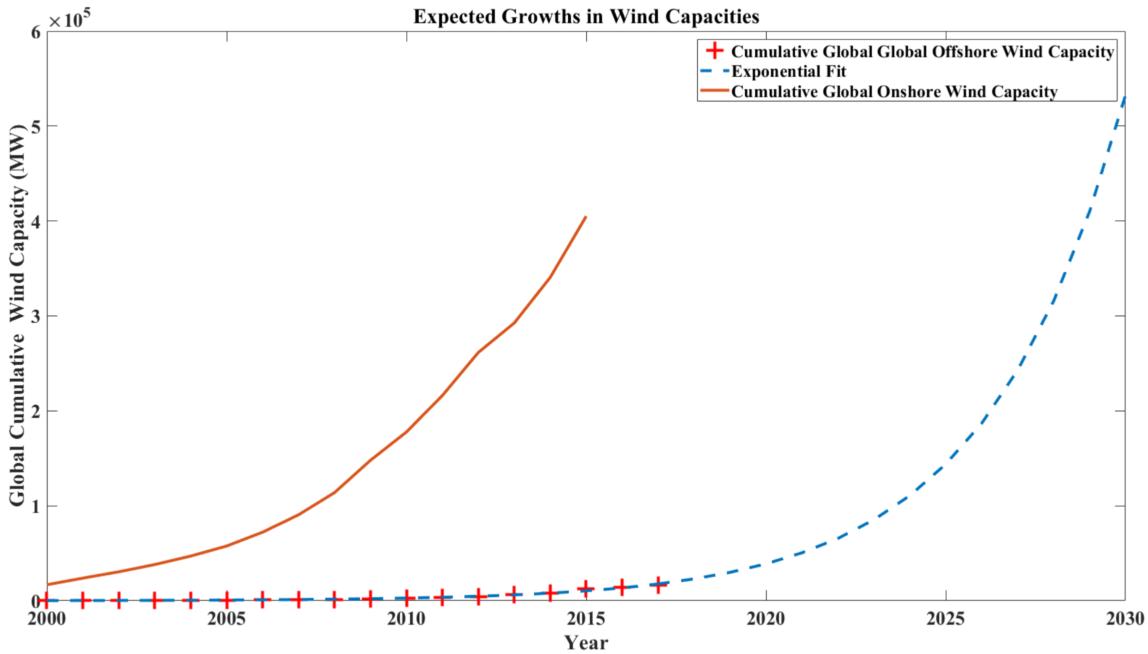

Figure 3: Expected Growths in Wind Capacities. Both onshore and offshore wind have experienced exponential growth in recent years. This implies that neither technology has reached the point of maturity where the implementation of the technology will slow, along with the benefits of learning. Onshore wind has much more installed capacity and, assuming the two curves have the same shape, is consequently further along its technology life cycle.

We explore how the maturity of different components of offshore wind turbines affects the LCOE. To do so, we treat an offshore wind turbine as a hybrid technology, separating it into two primary parts, “mature” technologies (everything above the water), and “emerging” technologies (everything below the water). To test this model, we treat the components of a wind turbine that lie above the water to be like onshore wind turbines, which have been in production for much longer than offshore wind turbines.

With the exception of specific considerations for external conditions, such as weather, ocean stresses, and other marine environment factors, the design of offshore wind turbine rotor-nacelle assembly closely mirrors that of its onshore counterpart [11].

Analyzing the minute effects of the maturity of these individual technologies exceeds the scope of this thesis but may provide further insights. The structures that support offshore wind turbines, however, differ significantly from those that support onshore wind turbines.

There are two primary categories for offshore wind turbine support structures: fixed bottom, and floating. Figure 4, below, shows a diagram of a fixed bottom turbine, and Figure 5 shows diagrams of three types of floating offshore wind turbine: spar, tension leg platform, and semisubmersible. Figure 4 is from IEC 61400-3-1, and Figure 5 is from IEC 61400-3-2. IEC 61400-3-1 and IEC 61400-3-2 are international wind turbine standards [23]. For this thesis, we treat the tower, platform, and rotor-nacelle assembly as onshore wind-like technologies. For fixed bottom turbines, we treat the foundation, pile, and sub-structures as emerging technologies. For floating turbines, we treat the floating sub-structures, piles, and mooring as emerging technologies [24].

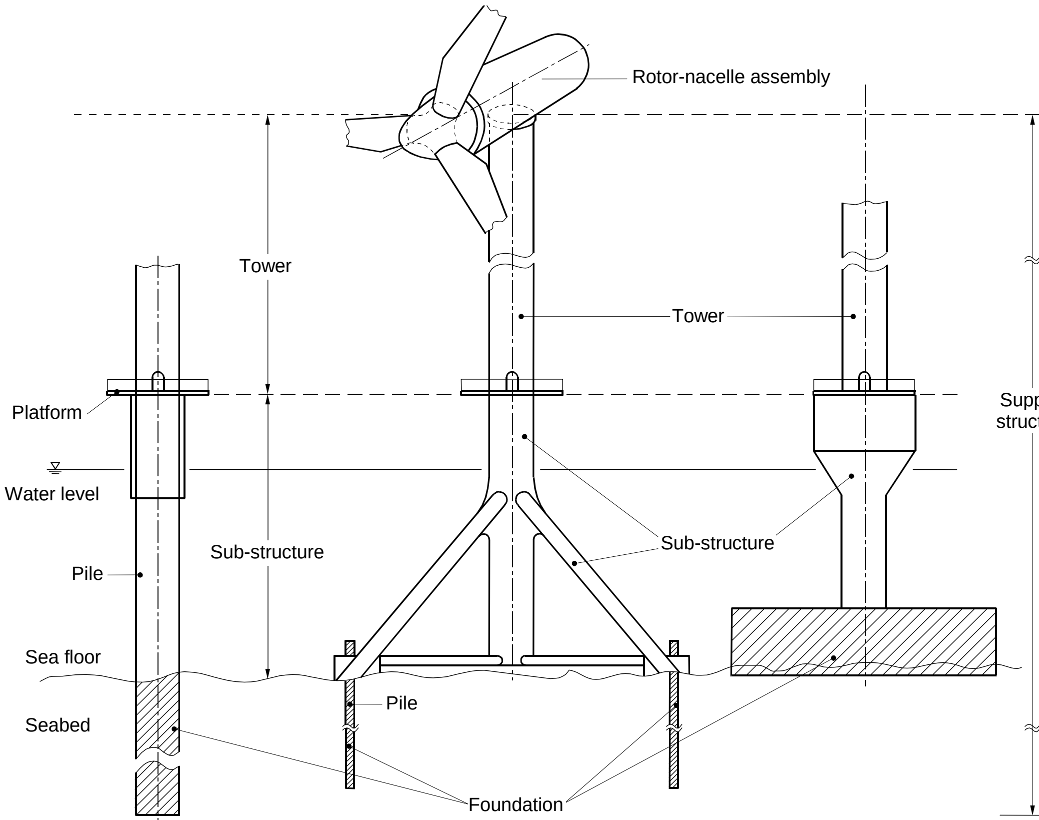

Figure 4: Parts of a Fixed Offshore Wind Turbine. This figure is from IEC 61400-3-1.

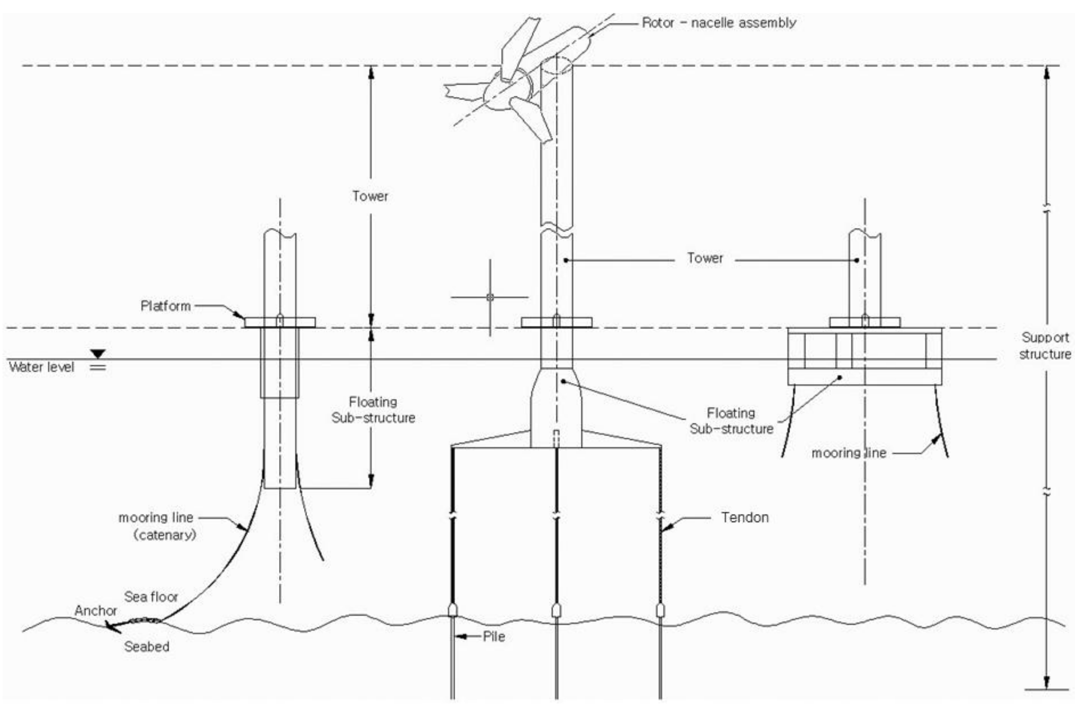

Figure 5: Parts of a Floating Offshore Wind Turbine (FOWT). From left to right: Spar, Tension Leg Platform, and Semisubmersible. This figure is from IEC 61400-3-2.

Our first step to examine the effects of maturity in the two component technologies is to understand their historical impacts. On average, considering the different support structures, the mature technologies contribute roughly 40% of the capital cost and the emerging technologies contribute roughly 60% [25-27]. This value changes from year to year, as seen in Table 1 [25,28-31]. Also seen in Table 1, the contributions from each technology do not change much in relation to each other from 2011 to 2017. This may suggest that the mature technologies are learning at rates comparable to the emerging technologies. We explore this idea in later chapters.

Table 1: Historical Technology Contributions to Offshore Wind LCOE

Year	**Mature Technology Contribution**	**Emerging Technology Contribution**
2011	38%	62%
2013	38%	62%
2015	33%	67%
2016	35%	65%
2017	36%	64%

We apply these ratios to the historical offshore wind LCOE data from 2011 to 2017 to find the historical contributions to LCOE from the mature and emerging technologies ($C_{t,m}$ and $C_{t,e}$ respectively), as seen in Equation 6, where k is a binary variable representing either a mature technology, m, or an emerging technology, e, t is the year, $W_{t,k}$ is a coefficient representing the fraction of the LCOE attributed to technology k in year t, and $C_{t,k}$ is the portion of the LCOE associated with technology k in year t. As such, for any given t in this time period, the total $LCOE_t$ of offshore wind is the sum of $C_{t,m}$ and $C_{t,e}$, as seen in Equation 7.

$$C_{t,k} = W_{t,k} * LCOE_t \quad (6)$$

$$LCOE_t = C_{t,m} + C_{t,e} \quad (7)$$

With the cost of a reference turbine in the historical time period, we then forecast the cost of the reference turbine for any other given time, represented as an increase in installed capacity, using learning curve methodology. We again use Wright's Method, Equation 1, to find projections for future values of $C_{t,m}$ and $C_{t,e}$, shown in Equation 8. Here, t represents the year, $N_{t,k}$ represents the cumulative capacity in year t for technology, k, and $C_{t,k}$ represents the cost of production at capacity $N_{t,k}$. The primary difference between the two types of technologies is the initial capacity, $N_{0,k}$. $N_{0,m}$ includes the cumulative capacities of both onshore and offshore wind energy. N_{0e} on the other hand, only includes the cumulative offshore capacity. The new capacities, $N_{t,k}$, will be greater than the respective initial capacities, $N_{0,k}$, such that the relation in Equation 9 is true, where $G_{k,t}$ represents the growth in technology k. This shows the effects of learning from building offshore turbines, while accounting for onshore turbines that have been built previously. The learning rates, b_k are estimated by performing a least-squares fit on the logs of the capacity and LCOE data.

$$C_{t,k} = C_{0,k} * \left(\frac{N_{t,k}}{N_{0,k}}\right)^{-b_k} \quad (8)$$

$$N_{t,k} = N_{0,k} + G_{k,t} \quad (9)$$

With this in mind, we create a model to forecast the LCOE under an assumption that offshore wind is a hybrid technology, with both emerging and mature aspects. The purpose here is to produce a forecast to compare with elicitations, based on an estimation of what the experts would have known at the time of the elicitations. This model considers both the offshore and onshore capacities in year t. We choose 2014 as the reference year, t_0, for our calculations as this is the most recent data at the time the expert elicitations took place and makes for an easy comparison between the two forecasts. In this scenario, we apply the same learning rate to both technologies, rather than trying to estimate a learning rate from the data. This allows us to analyze the effects the difference in capacities has on the learning.

We summarize our two forecast models in Table 2, below. In our first model, where we treat offshore wind as a purely emerging technology, we use 2011 as our reference year, t_0, as this is where we begin to see the effects of learning. The initial capacity and capacity growth for the emerging technology, $N_{0,e}$ and $G_{0,e}$, are taken to be the global capacity of offshore wind in 2011, 3,336 MW, and the growth in capacity during the years following, on the order of about 1,000 MW per year. The initial capacity and capacity growth for the mature technology, $N_{0,m}$ and $G_{0,m}$, are not applicable in this model.

For comparison, in our second model, where we treat offshore wind as a hybrid technology, we use 2014 as our reference year, t_0. The initial capacity and capacity growth for the mature technology, $N_{0,m}$ and $G_{0,m}$, are taken as the globally installed capacity of onshore wind in 2014, 261,530 MW, and the growth in onshore wind capacity during the years following that, on the order of about 10,000 MW per year. $N_{0,e}$ and $G_{0,e}$ in the hybrid technology model reflect growth in offshore wind only, like those in the emerging technology model, except for the reference year. $N_{0,e}$ is taken as 7,787 MW, the global capacity of offshore wind in 2014, and $G_{0,e}$ is taken as the growth in offshore wind in the years following 2014, also on the order of about 1,000 MW per year.

For the emerging technology model, we fit historic data to estimate the index of learning. For the hybrid technology model, we use an assumed index of learning, $-b = -.18$, to see how maturity affects cost. This is the same index of learning we find in the emerging technology model.

Table 2: Offshore Wind Forecast Models

Variable	**Offshore Wind as an Emerging Technology**	**Offshore Wind as a Hybrid Technology**
t_0	2011	2014
$N_{0,e}$ **(MW)**	Offshore wind capacity: 3,336	Offshore wind capacity: 7,787
$N_{0,m}$ **(MW)**	N/A	Onshore wind capacity: 261,530
$G_{e,0}$ **(MW/year)**	Growth in offshore wind capacity: O(~1,000)	Growth in offshore wind capacity: O(~1,000)
$G_{m,0}$ **(MW/year)**	N/A	Growth in onshore wind capacity: O(~10,000)

2.3 Expert Elicitation Comparison

Expert elicitations aggregate expert opinions and are crucial when data is sparse, as they can fill in knowledge gaps [32]. Offshore wind is a young technology, compared to traditional energy production technologies, such as coal and oil. By comparing the historical data of our experience curves with the predictive data of expert elicitations we further expand our data set and can better understand the trends we see in offshore wind LCOE as well as the drivers of those trends.

We build a figure like Figure 1 in Nyqvist et al. (2015), shown below as Figure 6 [7]. In their paper, Nyqvist et al. compare historical LCOE data of lithium-ion battery packs for battery electric vehicles (BEV) with expert elicitations of future LCOE values. Similarly, we combine historical data for offshore wind LCOE with expert elicitations of the future of offshore wind LCOE collected by and presented in Wiser et al. 2016 [12].

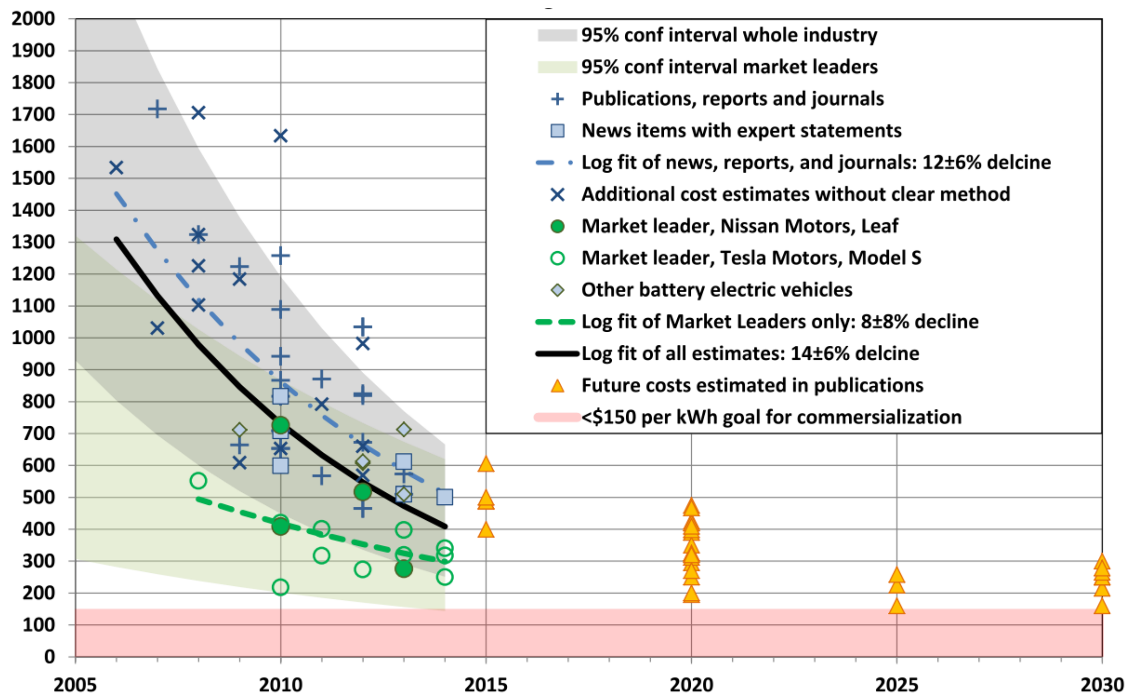

Figure 6: Example Learning Curve and Expert Elicitation. A marriage of backward-looking historical data and forward-looking expert elicitation data, taken from Nyqvist, et al. (2015). The blue and green crosses and circles represent historical data. The black line and blue and green dashed lines represent log fits of the historical data. The yellow triangles represent expert elicitations. By comparing the historical and forward-looking data sets, researchers can better understand both and draw better conclusions from their data.

CHAPTER 3

DATA

In Chapter 3, we describe our data. We begin by discussing the sources of our data for the turbine experience curves. In Chapter 3.1 we discuss the data we use to construct the offshore wind learning curve, where we treat offshore wind as an emerging technology, and in Chapter 3.2, we discuss the data we use to construct the alternative learning curve, where we consider offshore wind to be a hybrid technology. This is followed by describing data collection for the expert elicitations, Chapter 3.3.

3.1 Offshore Wind

Our data, for the offshore wind experience curve, come from various reports, papers, and institutions. They represent the history of offshore wind and span several regions but reside primarily in Europe. Table 3 lists the offshore wind data sources, the years, countries, and number of projects they cover, and the data they provide.

Table 3: Offshore Wind Data Sources

Source	**Years**	**Data**	**Locations**	**Number of Projects**
Smith, et al. (2015) [33]	2000-2015	Capital Expenditure, Capacity Factor, Capacity	UK, Germany, Denmark, Belgium, Netherlands, Sweden, Japan, Finland, Ireland	41
MacGilivray, et al. (2014) [34]	2000-2012	Capital Expenditure	UK Denmark	21
van der Zwaan, et al. (2012) [35]	2000-2008	Capacity Capital Expenditure	Europe	11
Hawila, et al. (2017) [36]	2010-2017	Cumulative Capacity LCOE	Denmark, China, UK, Italy, Netherlands	9
Remy, et al. (2018) [37]	2017	Capacity	UK, Germany, Belgium, Finland, France	17
4C Offshore [38]	2015-2016	Capacity	Germany, UK	15

Some of the capacity factor and capital expenditure data in Smith et al. (2015) lacks information regarding the location of the wind farm. This is illustrated in

4, below, as a sample of the data supplied in the paper [33]. In these cases, we assume that these projects refer to projects reported in that paper's capacity data, and using the years associated with the projects, we match the country-ambiguous capacity factor and capital expenditure data with the capacity data. To be consistent, we assume the smallest projects, in terms of capacity, have the largest capital expenditure and the smallest capacity factor. This assumption models building larger projects where the resources are more prevalent, thus maximizing the electricity production.

Table 4: Smith Data Ambiguities Sample

Country	Commercial Operation Data (year)	Capacity Factor
United Kingdom	2017	33%
United Kingdom	2017	37%
Other	1997	26%
Other	2000	34%
Other	2001	18%

3.2 Onshore Wind

To conduct analysis into the effects of component maturity, we use capacity data for both onshore and offshore wind from 2011 until 2017 [39,40]. These capacities are listed in Table 5 for both onshore and offshore capacities. As the table shows, the global installed capacity for onshore wind is much larger than that of offshore wind, 32 times larger in the most recent years. We also note that onshore wind capacity is growing faster than offshore wind in terms of magnitude. From year to year, onshore wind capacity grows on the order of 10,000 MW while offshore wind capacity grows on the order of 1,000 MW. Compared to their capacities in 2011, however, offshore wind has seen more relative growth, experience almost a 5-fold increase compared to onshore wind’s 2.7-fold increase in the same time span.

Table 5: Historical Capacities for Onshore and Offshore Wind

Year	Onshore Wind Power Capacity (MW)	Offshore Wind Power Capacity (MW)
2011	147,960	3,336
2012	177,750	4,034
2013	216,190	6,269
2014	261,530	7,787
2015	292,630	12,685
2016	340,610	14,138
2017	405,020	16,557

We then use the historical estimates of LCOE contribution from the mature and emerging technologies and learning rates we establish from our experience curve to forecast the future contributions.

3.3 Expert Elicitation

To create our analog to Figure 6, we use backward-looking historical data and forward-looking expert elicitation data. We use the data we have gathered for the turbine experience curves, described in Chapters 3.1 and 3.2, for historical data. For the expert elicitation data, we use data collected by Wiser et al. (2016) [12]. They conducted expert elicitations on the LCOE of wind power, both onshore and offshore, eliciting responses from 163 experts in the wind energy field. Included in their data are 110 expert responses regarding the LCOE of fixed bottom offshore wind turbines and 44 expert responses regarding the LCOE of floating offshore wind turbines. This study emphasized costs in 2030 [12].

Between October 2015 and December 2015, the experts submitted predictions for the LCOE of onshore, fixed bottom offshore and floating offshore wind turbines for 3 years: 2020, 2030, and 2050. For each of these years, the experts predicted three LCOEs: a high, a median, and a low (90^{th} percentile, 50^{th} percentile, and 10^{th} percentile respectively). Thus, we have 154 estimates for offshore wind LCOE for three years and three scenarios, resulting in almost 1400 data points.

CHAPTER 4
RESULTS AND ANALYSIS

In this chapter, we detail our results. In Chapter 4.1, we discuss results from the experience curve analysis, in Chapter 4.2, we discuss results from the maturity analysis, and finally, in Chapter 4.3, we discuss results from the expert elicitation comparison.

4.1 Emerging Technology Model

In this chapter, we build two global experience curves for offshore wind turbines, Figure 7 and Figure 8. Figure 7, in Chapter 4.1.1, is the global experience curve with all the projects aggregated by the year they were completed and weighted by the capacity of the farm, from 2000 to 2017, for a total of 18 data points. That is, we show only the total capacity and the average cost for each year. In Figure 8, shown in Chapter 4.1.2, we show each individual project, plotting LCOE and global cumulative installed capacity for each.

4.1.1 Aggregated Data

Figure 7 shows a slight decrease in LCOE in the early period, from 2000 until about 2003. This early trend coincides with the expected effects of benefitting from learning by doing [9]. From 2003 until about 2011, however, the LCOE of offshore wind turbines increases. This increase contrasts with the expected effects of learning by doing.

Smith et al. (2015) has also made note of the increasing trend in offshore wind LCOE prior to 2011. They suggest that it is due to factors such as installing turbines further from shore and in deeper waters, shortages in the supply chain, including components, vessels, and skilled labor, increasing prices for commodities, and more conservative pricing strategies on the part of equipment suppliers and installation contractors [33]. Offshore wind is not the only industry to experience negative learning during the early phases of development. The nuclear industries of both France and the United States saw increases in electricity costs during early development [41]. On a global scale, the same can be said for gas turbine combined cycle power plants [42].

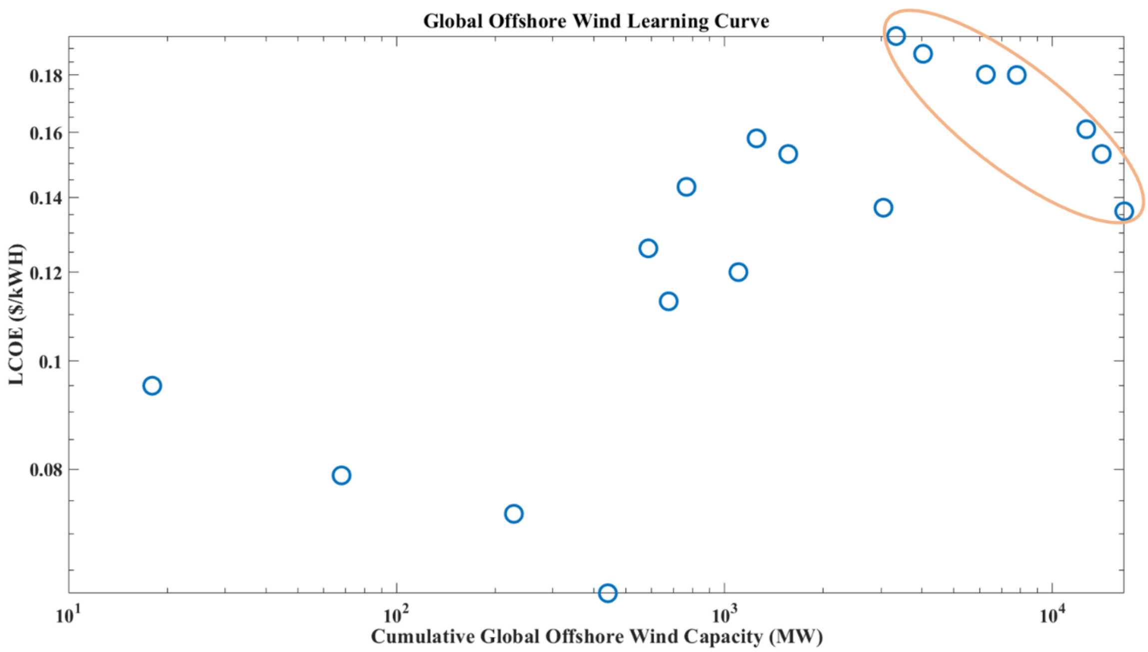

Figure 7: Global Offshore Wind Learning Curve. The upward trend from 2003 to 2011 implies that the cost of electricity produced by offshore wind turbines is increasing, despite the benefits of learning, potentially due to installing turbines further from shore. After 2011, the benefits of learning appear to take effect, beginning to reduce the LCOE of offshore wind power, shown here in the orange circle.

The period of negative learning is followed by a period of positive learning. From 2011 until the most recent data, 2017, the data points circled in orange, the LCOE of offshore wind power decreases, following the expected trend of learning by doing, suggesting the industry is finally reaping the benefits of learning. During this period, the learning rate is 12.4%, meaning that for every doubling of capacity we expect a reduction in cost of 12.4%. For comparison, according to Nagy et al., the learning rate for onshore wind from 1984-2005 was 12% [43]. This implies that offshore wind is following a trajectory very similar to that of onshore wind.

4.1.2 Disaggregated Data

To better understand the trends in LCOE of offshore wind, we plot the LCOE of the individual projects against the cumulative globally installed capacity and superimpose the global trend for comparison, Figure 8. By not aggregating the data, we have more data points to examine. In addition to this, by grouping the projects by country, we can examine regional trends as well as the general global trend.

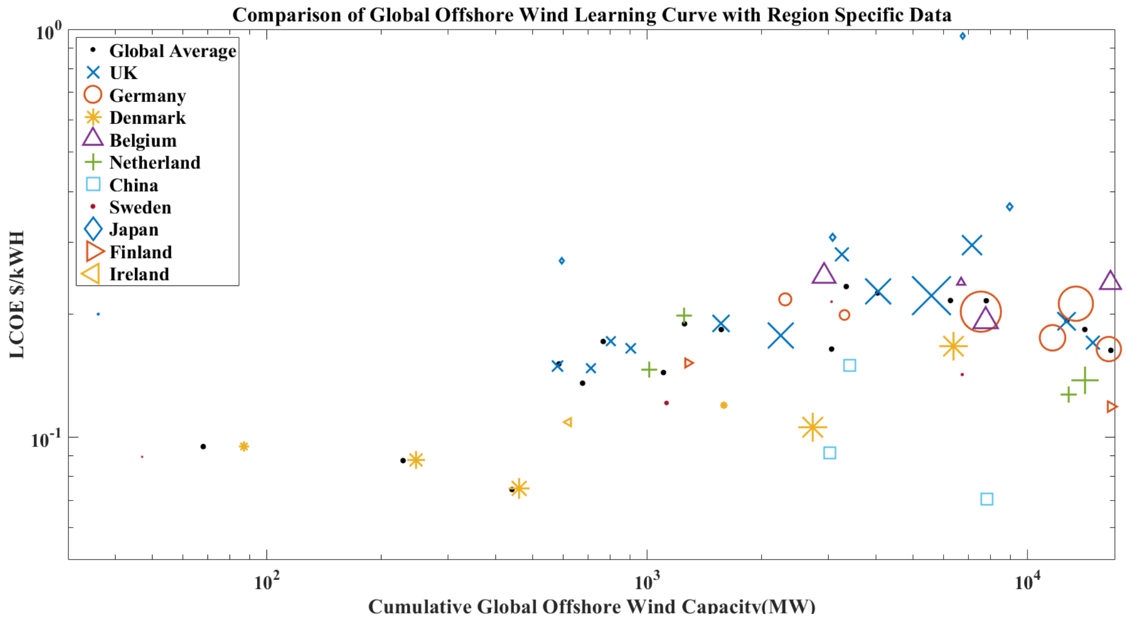

Figure 8: Comparison of Global Offshore Wind Learning Curve with Region Specific Data. The overall global trend seems to follow the aggregate trend (black dots), apart from some outliers, but the individual regional trends appear to have slightly more scatter, suggesting that learning is more consistent on a global scale than it is on a regional one. The individual projects are scaled by the size of the project such that larger symbols represent larger capacity projects. The largest projects appear to drive the global trends.

Figure 8 shows the same initial decrease in LCOE that Figure 7 showed. Unlike Figure 7, however, Figure 8 shows that this trend is made up of only five data points, three of which belong to Denmark. The subsequent increase and decrease of LCOE, after 2003 and 2011 respectively, however, are supported by most of the data. We also note that China and Japan appear to be outliers compared to the rest of the countries. Due to the small size of these projects, denoted by the relative sizes of the markers, however, in comparison with the total capacity in the years they were built, the effects of removing these outliers results in less than a 5% difference in LCOE.

Our results show that, on a global scale, the LCOE of offshore wind increased from 2003 to 2011 and decreased from 2011 until present. Regional trends, such as that seen in the UK, however, do not necessarily follow the global trend. The benefits of learning do not appear in the UK until 2013, two years after the global shift from negative to positive learning. In fact, no country exactly follows the global trend. This may suggest that learning is more consistent on a global scale than it is on a regional one, potentially due to delays in knowledge spillover from country to country.

The capital costs, which are proportional to the LCOE, increase from 2003 to 2011. Some factors that increase the capital costs should also increase the capacity factor, potentially lowering the LCOE [33]. For example, wind resources are more plentiful further from shore. On average, the winds are faster and more consistent. However, the costs of building and maintaining turbines also increases as the distance from shore increases [44], countering the benefits of increasing the capacity factor, we explore this more in Chapter 4.1.3.

4.1.3 Relationship Between LCOE and Capacity Factor

As stated in the previous chapter, LCOE is very closely related to capacity factor. Increasing the capacity factor of an offshore wind turbine allows operators to produce and sell more electricity, ideally lowering their costs [45].

In Figure 9, we examine the relationship between LCOE and capacity factor. We use capital expenditure as a stand in for LCOE as it is the primary factor in our calculations as described in Chapter 2. We find, on a global scale, there is no meaningful correlation between capital expenditure and capacity factor. On a regional scale, however, we find stronger correlations. These correlations are listed in Table 6. Some regions likely have access to stronger or more easily accessible wind resources. This would lead to smaller capital expenditures for similar capacity factors, essentially smearing the correlations across the capital expenditure axis when comparing across the globe.

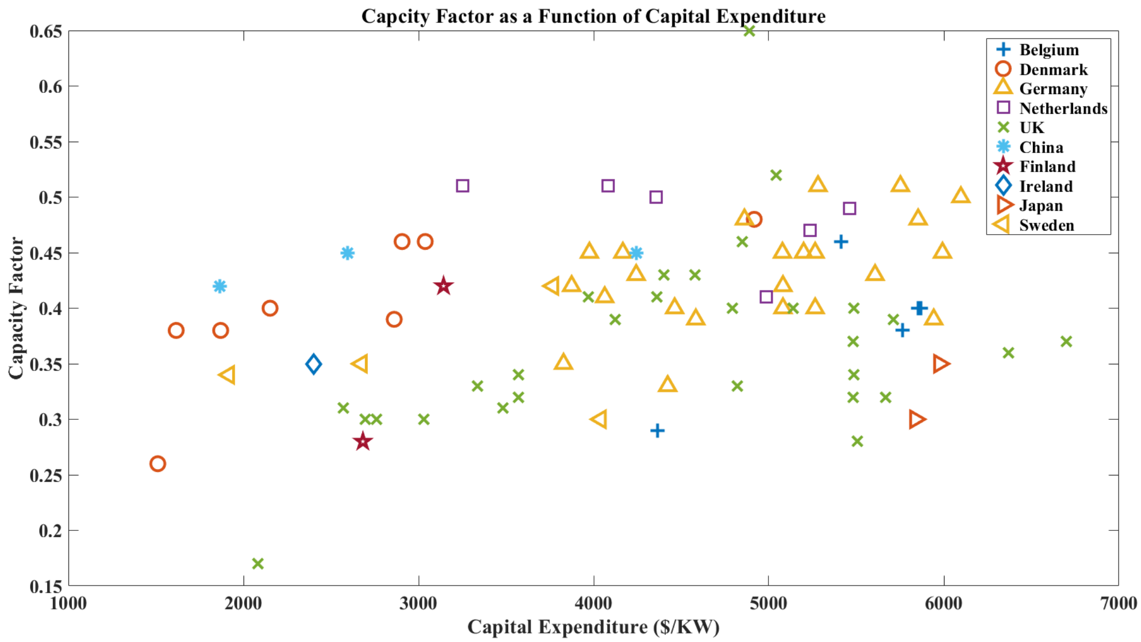

Figure 9: Comparing Capital Expenditure and Capacity Factor. There is no meaningful correlation between capacity factor and capital expenditure on the global scale. Regionally, however there appears to be stronger correlations.

Table 6: Correlations Between Capital Expenditure and Capacity Factor

Country	**Correlation Coefficient**
China	.74
UK	.60
Denmark	.76
Belgium	.71

The relationship between the capacity factor and the capital cost is multi-faceted. As stated previously, developers have begun installing turbines further from shore to take advantage of the greater and more reliable wind resources, which should increase capacity factor by allowing the turbines to run at or near capacity more often [44]. In addition to this, since 2000, the average rotor diameter on offshore wind turbines has nearly tripled [46]. The trend of increasing rotor diameter can increase the maximum power a turbine can generate, but it can also increase operations costs. Longer blades can have larger deflections from flapwise forces and put more stress on their components [47]. Excess stress can lead to more maintenance, and subsequently down time to perform the maintenance, and thus a lower capacity factor [48].

Regionally, the potential increase in capital costs is not without benefit, however. As the rotor sizes increase and developers take advantage of the wind resources further from shore, the increase in generation has the potential to outweigh the costs. The relationship between rotor size and power generation is not linear. The available wind power is given by Equation 10, where c_p is the rotor's power coefficient, ρ is the density of the air, A is the area swept by the rotor, U is the wind speed, μ_m is the mechanical efficiency, and μ_e is the electrical efficiency [11].

$$P = \frac{1}{2} * c_p * \rho * A * U^3 * \mu_m * \mu_e \qquad \textbf{10}$$

The power available in wind is proportional to the swept area, which is proportional to the square of the radius of the rotor. As such, an increase in rotor diameter will result in an even larger increase in the swept area, and thus the power. It can also be seen from Equation 10, that the available power is proportional to the cube of the wind speed, thus enticing developers to install wind turbines further from shore where the wind speed is greater. Wind turbines are limited by the capacity of the installed generator. As such, stronger winds may not necessarily produce the maximum of the power available in the wind. These stronger winds are likely more reliable, however, thus allowing the turbines to operate near capacity for a greater percentage of time, thus producing more electricity and lowering costs.

On one hand, increasing the capital expenditure of projects can result in higher capacity factors on a regional scale. This allows the turbines to produce more electricity, but it also has to compete with the maintenance required to keep the turbines in working order. Increasing the capacity factor of offshore wind turbines is vital to ensuring offshore wind's ability to compete with established energy technologies and could contribute to lowering the per MW cost of offshore wind.

4.2 Hybrid Technology Model

The results in Chapter 4.1 assume the offshore wind is purely an emerging technology, with all its components learning rapidly, Equation 1. As stated previously, offshore wind may be a hybrid of mature and emerging technologies. To explore this concept, we apply the learning rate methodology to the different types of technology. The technologies are at different points in their respective experience curves and thus will have different values for installed capacity. We assume learning in the emerging technologies is based solely on the cumulative installed capacity of offshore turbines. On the other hand, we assume the learning in the mature technologies is based on the sum of the cumulative installed capacities of both offshore and onshore wind turbines, which is significantly larger, Equation 8.

In Figure 10, we explore some of the differences between the emerging and hybrid technology models summarized in Table 2 . The higher lines show forecast LCOEs for the emerging part of offshore wind. The blue line is the emerging technology model and the yellow line is the hybrid technology model. The emerging technologies behave similarly in both models. Recall, the primary difference between these models is the cumulative capacities of the mature and emerging components of offshore wind, the sum of offshore and onshore wind capacities for the hybrid technology model and solely the capacity of offshore wind for the emerging technology model. The models also start at different reference years, 2011 for the emerging technology model and 2014 for the hybrid technology model.

The disconnects in the blue and red lines are artifacts of switching from historical to forecasted data. In the blue line, the LCOE of the emerging components in 2017 (the last point in the first part of the line) is less than what is expected from the fit used for the forecast (the first point in the second part). The red line, on the other hand, has a slightly higher LCOE than would be forecast from the fit. The yellow and purple lines do not have disconnects as these lines are fits to a hypothetical scenario.

The mature portions, the red and purple lines, behave very differently from each other from model to model. In the hybrid technology model, the mature technologies show slower learning in response to a much larger cumulative capacity, the sum of offshore and onshore cumulative capacities. The contributions from the mature and emerging technologies in the hybrid model approach each other in the later years, as the emerging technologies transition to mature technologies. The red line does not experience the same deceleration of learning because we consider its cumulative capacity to be solely that of offshore wind. Its shape is a result of being treated as an early emerging technology.

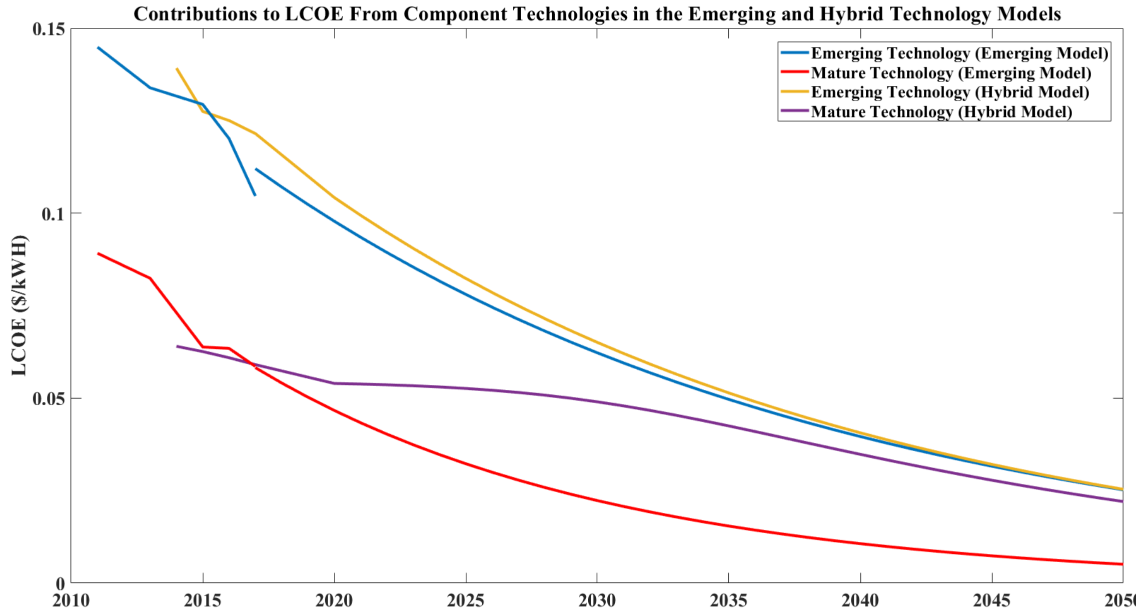

Figure 10: Contributions to LCOE From Component Technologies in the Emerging and Hybrid Technology Models. In the emerging technology model, the two component technologies behave like emerging technologies. In the hybrid technology model, the two technologies behave differently and approach each other in the later years.

To fully understand how the behavior of the mature technologies affects the LCOE of offshore wind, we plot the learning curves for the emerging technology and hybrid technology models in Figure 11. Here, the black line represents the emerging technology model and the blue line represents the hybrid technology model. The black crosses represent historic offshore wind LCOE data. In either case, the line is the sum of contributions to offshore wind LCOE from the mature and emerging technologies described in Equation 7. The hybrid technology model predicts less learning than the emerging technology model. This is because the hybrid technology model assumes the learning experienced by the mature technologies will slow, especially in comparison to the emerging technologies. The emerging technology model assumes the entire technology is emerging, and thus has higher overall learning.

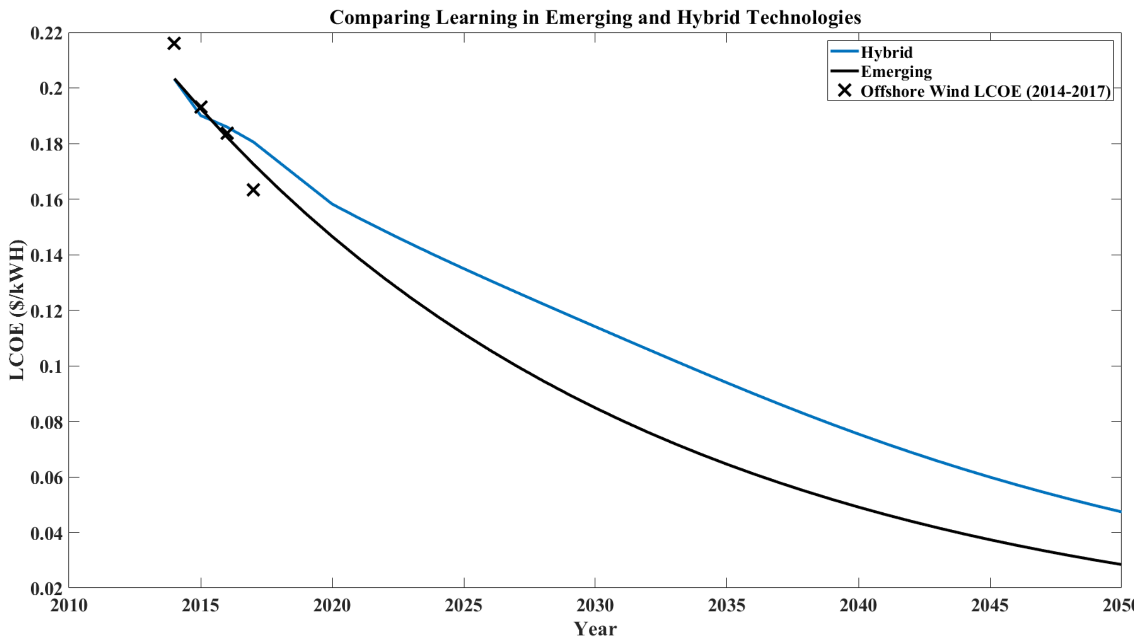

Figure 11: Comparing Learning in Emerging and Hybrid Technologies. The blue line represents the hybrid technology model and the black line and crosses represent the emerging technology model.

4.3 Expert Elicitation Comparison

To better understand the potential future trends of offshore wind power prices, we create a robust and extensive data set, marrying historical data with forward looking expert elicitations. We compare our forecasts of offshore wind LCOE from the emerging technology and hybrid technology models (the historical data) with the forward-looking, expert elicitation data. Figure 12 maps the passage of time to the evolution of LCOE.

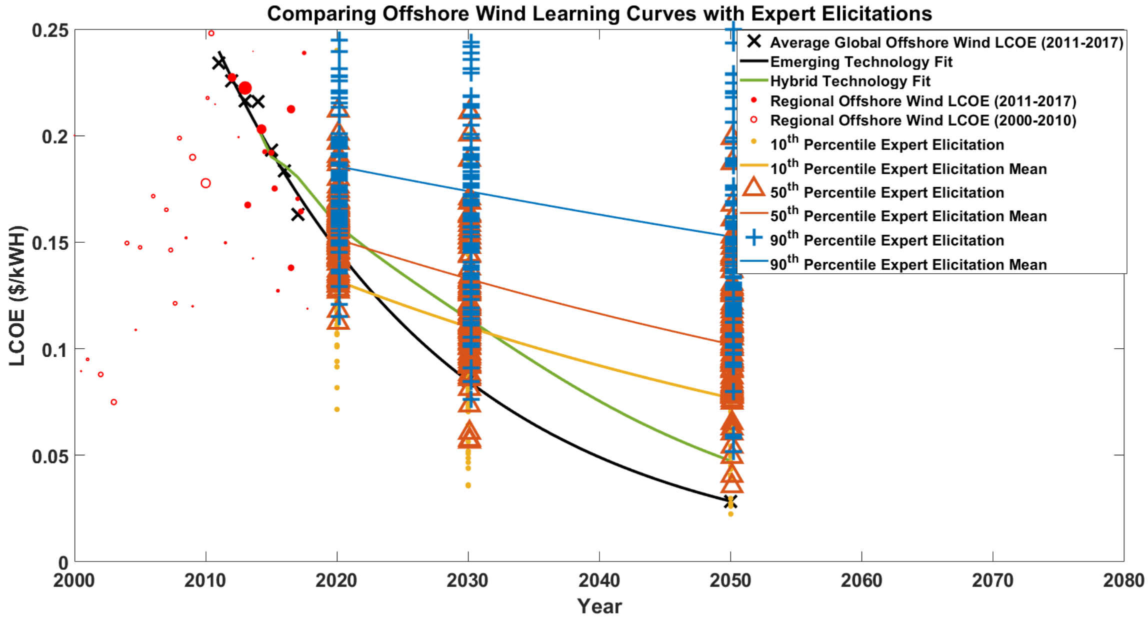

Figure 12: Comparing Offshore Wind Learning Curves with Expert Elicitations. The red rings represent historical offshore wind projects built prior to 2011. The red circles represent historical offshore wind projects built after 2011. The size of the circle or ring represent the relative size of the project. The black crosses represent global average LCOE after 2011 and the black line is an exponential fit to that data (emerging technology model). The green line is the hybrid technology model. The blue crosses, orange triangles, and yellow dots represent expert elicitation data for 90th, 50th, and 10th percentile expert elicitation scenarios, respectively. The blue, orange, and yellow lines represent exponential fits to the mean of the three expert elicitation scenarios.

The red rings represent historical offshore wind projects built prior to 2011. The solid red circles represent historical offshore wind projects built after 2011. In either case, a larger ring or circle represents a larger project in terms of capacity. The black crosses represent average global LCOE for offshore wind and the black line is an exponential fit to this data, the emerging technology model. The green line represents the hybrid technology model described in Chapter 4.2.

The blue crosses, orange triangles, and yellow dots represent expert elicitation data in 10th, 50th, and 90th percentile forecasts for fixed bottom wind farm LCOE respectively. Note that the experts were forecasting a “typical” or median wind farm. The blue, orange, and yellow lines are exponential fits of the mean of each of the three scenarios.

There are two important things to note. First, after 2030, both the black historical curve and the green historical curve lie below all three of the averaged elicitation curves. Our models predict lower LCOE than the average expert. Second, the black curve appears to decrease more quickly than any of the colored curves. This implies that the historical learning trends are more prominent than the average expert would expect.

In both models, the experience curve generated from historical data predicts more learning and lower LCOE than the averages of the expert elicitations. However, our emerging technology model LCOE prediction for 2020 lies between the mean of the 10^{th} and 50^{th} percentiles of the expert predictions. The hybrid technology model is very close to the mean of the 50^{th} percentile of the expert predictions for 2020 and does not fall below the mean of 10^{th} percentile expert prediction until after 2030. The fact that the hybrid technology model matches more closely with the expert elicitation data may suggest that they also considered parts of offshore to be subject to mature learning.

Another potential explanation of the discrepancies between our models and the expert elicitation data is that the experts were asked to predict LCOE for a “typical”, or median, turbine. It is possible that the data used to construct our historical models represents turbines in the “best” locations, those that are easiest to build in or have the strongest resources. If this is the case, our models predict the lower bound of offshore wind LCOE and the true values would likely be higher. A deeper analysis of this is difficult as turbines closer to shore are less expensive to construct but have access to less reliable wind resources than turbines built further from shore, and thus are likely to produce less electricity. As such, studying the costs and benefits of turbine placement could provide further insight into LCOE predictions but exceeds the scope of this thesis.

CHAPTER 5

CONCLUSION AND RECOMMENDED FUTURE WORK

The results of this study are promising for the future of offshore wind power. Offshore wind power is expected to decrease in cost across all models. As offshore wind LCOE continues to decrease, it will become easier for policy makers to promote it as a decarbonization strategy. Offshore wind power shows strong potential as a promising green energy investment and an affordable power source.

While our emerging technology model does not match the projections of the experts elicited in Wiser et al., the discrepancy is not the end of the story, especially considering that our hybrid technology model projection lies well within the lower half of the experts' projections. Historically, offshore wind LCOE has been decreasing faster than experts had anticipated. We do not know the full set of assumptions each expert forecasted under, or how these assumptions played out. It would be interesting to see if this phenomenon is unique to offshore wind or if it appears in other technologies.

Historical trends in offshore wind suggest that it is behaving like an emerging technology. As such, it is possible that, while onshore wind has significantly more cumulative capacity than offshore wind, components shared between the two technologies may still benefit from learning. Or, perhaps there is little spill over between offshore and onshore wind, meaning learning takes place independently in the two technologies. Finally, a likely explanation is that learning is at the system level, with important interactions between the components. Future efforts could help explain the similarities and differences in the two technologies.

The full set of projections, consisting of our emerging and hybrid technology models and the experts' LCOE projections, serves as bounds on the expected LCOE of offshore wind and creates a robust dataset from which decisions regarding investment and support for offshore wind can be made. This data set provides policy makers and researchers with a rich resource to draw from as new studies and policies are developed.

Additionally, the benefits of learning from developing and producing a technology are not as simple as assuming that every piece of the technology develops in unison. While this complexity adds some uncertainty to the conversation, it also provides opportunity for further learning and advancement through specialization in production of various technologies that go into offshore wind farms.

More work can be done, however, to further understand the trends and drivers behind the cost of offshore wind power. We present a best-case scenario where every piece of the offshore turbine benefits from learning, as well as a broad look into how the maturity of different technologies within the turbine can affect the benefits of learning. Deeper studies should be conducted to look for correlations between learning, and, consequently, prices, of specific technologies that comprise offshore wind farms beyond the broad categories of mature and emerging.

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